Time-Varying Liquidity and Momentum Profits*

Doron Avramov

Si Cheng

and

Allaudeen Hameed

Current Draft: October 6, 2014

---

* Doron Avramov is from The Hebrew University of Jerusalem (email: doron.avramov@huji.ac.il); Si Cheng (email: s.cheng@qub.ac.uk) is from Queen's University Belfast, and Allaudeen Hameed (email: allaudeen@nus.edu.sg) is from National University of Singapore. We thank Yakov Amihud, Constantinos Antoniou, Mike Cooper, Tarun Chordia, Qianqian Du, Ro Gutierrez, Bing Han, David Hirshleifer, Sergei Sarkissian, Andriy Shkilko, Qing Tong, and seminar participants at the joint seminar of Aalto University and Hanken School of Economics in Helsinki, Erasmus, Hebrew University of Jerusalem, Hong Kong University of Science and Technology, Robeco Asset Management, Southern Methodist University, Tel Aviv University, Tilburg, Tsinghua University, University of Texas at Austin, Vienna University of Economics and Business, 2014 Asian Finance Association Conference, 2014 China International Conference in Finance and SGF Conference 2014 for helpful comments.

Abstract

A basic intuition is that arbitrage is easier when markets are most liquid. Surprisingly, we find that momentum profits are markedly larger in more liquid markets. This finding is not explained by variation in macroeconomic condition, cross-sectional return dispersion, investor sentiment or by disposition-driven theory of momentum. The predictive performance of aggregate market illiquidity for momentum profits uniformly exceed that of market return and market volatility states. While momentum strategies are unconditionally unprofitable in US, Japan, and Eurozone countries in the last decade, they are substantial following liquid market states.

1. Introduction

The economic notion of limits to arbitrage suggests that the profitability of anomaly-based trading strategies should be lower when markets are liquid. The evidence concerning many of these anomalies has typically been supportive of this notion. For example, Chordia, Subrahmanyam, and Tong (2014) offer this interpretation of their finding that the recent regime of increased stock market liquidity is contemporaneous with the attenuation of equity return anomalies due to increased arbitrage. They find that the decrease in tick size due to decimalization in the U.S. stock exchanges has lowered trading costs and attenuated the profitability of prominent anomaly based trading strategies in the recent decade, consistent with the effect of greater arbitrage activities. To test more directly the role of liquidity for arbitrage, we examine the systematic relation between variations in market liquidity and the strength of the momentum anomaly (Jegadeesh and Titman (1993)).[1] We focus on momentum because it is a robust and well-known anomaly that is not explained as a risk premium, and therefore, is subject to arbitrage.

If variations in momentum payoffs reflect changes in arbitrage constraints, we expect a positive relation between momentum profits and aggregate market illiquidity. We find that the effect goes in the opposite direction, and strongly so. The evidence is that momentum profits are large (weak) when the markets are highly liquid (illiquid). On the basis of the Amihud (2002) illiquidity measure, time-series regressions reveal that a one standard deviation increase in aggregate market illiquidity reduces the momentum profits by 0.87% per month, over the 1928−2011 period. For perspective, the unconditional raw monthly long-short momentum payoff is 1.18% and the Fama-French alpha is 1.73%. Our findings are contrary to the intuition that arbitrage of the momentum anomaly is easier when markets are most liquid.

The negative momentum-illiquidity relation is also quite robust. For example, the findings survive controls for the time-series dependence of momentum payoffs on down market states ($DOWN$) as well as market volatility (see Cooper, Gutierrez, and Hameed (2004), Wang and Xu (2010), and Daniel and Moskowitz (2012)). Similar results emerge when the Amihud measure is replaced by the

[1] Different from the evidence in Chordia, Subrahmanyam and Tong (2014), we examine the time-varying nature of the relation between market liquidity and momentum payoffs.

illiquidity measure recently developed by Corwin and Schultz (2012). The predictive effect of market illiquidity is also significant when the sample is restricted exclusively to large firms, indicating that the findings are not limited to illiquid stocks that make up a small fraction of the aggregate market capitalization. A cross-sectional analysis applied to individual stocks further reinforces the negative illiquidity-momentum relation. The slope coefficients in the regressions of stock returns on their own lags are the lowest following illiquid market states.

To explore more deeply the dynamics of momentum and illiquidity, we examine the association between aggregate illiquidity and the difference in the degree of illiquidity of winner and loser portfolios. The momentum strategy goes long on winners (which tend to be liquid) and short on losers (which tend to be illiquid). A positive cross-sectional relation between illiquidity level and stock return (Amihud and Mendelson (1986) and Amihud (2002)) implies that loser stocks should earn *higher* return. We find that when markets are liquid, price continuations dominate the cross-sectional liquidity effects, hence, generating a positive momentum payoff. On the other hand, when the market as a whole is illiquid, the large illiquidity gap between the loser and winner portfolios further reduces the momentum payoff as the loser portfolio earns a much higher subsequent return. Consequently, momentum payoffs are considerably lower following illiquid markets.

The analysis is then narrowed to the most recent decade wherein technological developments have lowered the barriers to arbitrage and the unconditional momentum strategy yields insignificant profits, as noted in Chordia, Subrahmanyam, and Tong (2014). Remarkably, the momentum profitability resurfaces upon conditioning on the market states, particularly when the market is highly liquid. Although the introduction of decimal pricing in 2001 considerably reduced trading costs, we detect substantial remaining momentum profits after accounting for variations in aggregate market illiquidity. Specifically, the monthly momentum profits increases dramatically from −0.69 percent when markets are illiquid to 1.09 percent during relatively liquid market states.

Moreover, over the past decade, there is an almost identical predictive effect of the lagged market state variables on the profitability of the earnings momentum strategy. Indeed, earnings momentum payoffs are significantly lower following periods of low market liquidity, reducing market valuations, and high market volatility. Examining all these three market state variables jointly, the effect of aggregate market illiquidity dominates.

We consider the possibility that the stock market illiquidity is an indicator of the state of the real economy, as suggested by Naes, Skjeltorp, and Odegaard (2011), and that variation in momentum payoffs reflects time-varying expected returns over the business cycle (Chordia and Shivakumar (2002)). Specifically, we account for variations in the macroeconomic state variables, including the dividend yield, the default spread, the yield on 3-month T-bills, and the term structure spread. Our findings on the predictive effect of market illiquidity on momentum payoffs are unaffected by these measures of the macroeconomy. Similarly, our findings survive controls for the predictive effects of cross-sectional dispersion in stock returns on momentum payoffs (Stivers and Sun (2010)), implying that these state variables do not fully explain the negative relation between illiquidity and momentum profits.

The effect of liquidity is robust to, and partially subsumes the recent evidence that momentum payoffs depend on inter-temporal variation in investor sentiment, as documented by Stambaugh, Yu, and Yuan (2012) and Antoniou, Doukas, and Subrahmanyam (2013). The predictive effect of illiquidity on momentum payoffs is robust to the inclusion of the investor sentiment index of Baker and Wurgler (2006, 2007). When the equity market is illiquid, momentum is unprofitable in all sentiment states, and negative momentum payoffs are recorded even during optimistic states. Clearly, market illiquidity captures a unique dimension of the time-varying momentum profits.

When we extend the analysis to non U.S. markets of Japan and ten countries establishing the Eurozone, we find similar evidence of significant time-variation in momentum payoffs in relation to market states, volatility and illiquidity. While we find that price momentum is lower following $DOWN$ market states and high market volatility periods in Japan and the European markets, the state of market liquidity continues to be the dominant predictor of momentum payoffs. Most strikingly, while it is well known that momentum is unprofitable in Japan (e.g. Griffin, Ji, and Martin (2003) and Chui, Titman, and Wei (2010)), the strategy yields substantial and significant profits following periods of low market illiquidity.

These findings on the association between market illiquidity and momentum payoffs complement the important studies on the liquidity risk (beta) exposure of the momentum portfolio in Pastor and Stambaugh (2003), Sadka (2006), and Assness, Moskowitz, and Pedersen (2013). To separate the effects of liquidity risk, we construct momentum portfolios which are Pastor-Stambaugh liquidity-beta neutral. After limiting the exposure of our portfolios to liquidity risk, we continue to find a significant negative loading of market illiquidity state on momentum payoffs.

The negative momentum-illiquidity relation also helps to distinguish behavioral explanations of the momentum anomaly. In Daniel, Hirshleifer, and Subrahmanyam (1998), for example, investors overreact to private information due to overconfidence, which together with self-attribution bias in their reaction to subsequent public information, triggers return continuation. Consequently, when overconfidence, along with biased self-attribution, is high, there is excessive trading, and the momentum effect is strong. Although the model does not formally examine liquidity, it is natural to interpret periods of heavy trading as more liquid. This interpretation is reinforced by the point that when investors think highly of their ability to value the stock accurately, they will underreact to information in order flow of others and, hence, increase liquidity (Odean (1998)). Alternatively, during pessimistic periods, overconfident investors keep out of the market due to short-sale constraints, and thus reduce market liquidity (Baker and Stein (2004)). Under all these scenarios, market liquidity provides an indicator of investor overconfidence, and such overconfidence can in turn drive the variation in the momentum effect, implying an association between illiquidity and momentum.[2]

Grinblatt and Han (2005) present a model where momentum is driven by underreaction to information due to the disposition effect.[3] When a stock experiences good news (i.e. a winner stock), and the price rises above the purchase price, investors who display disposition effect exert sell

[2] The predictions of other behavioral models such as Barberis, Shleifer, and Vishny (1998) and Hong and Stein (1999) for momentum profits when conditioned on market illiquidity are more difficult to ascertain. For example, in the Hong and Stein (1999) model, momentum profits come from the gradual diffusion of private information across investors and the interaction between heterogeneous agents, i.e., newswatchers who exclusively rely on their private information and momentum traders who trade only on past returns. While private information diffusion may be slower in illiquid markets, the relation between momentum and market illiquidity also depends on the aggressiveness of the trading by momentum investors in different liquidity states.

[3] The disposition effect refers to the tendency for some investors to have a higher probability of selling winners (stocks that have risen in value since purchase), rather than losers. One explanation that has been offered is based on prospect theory, in combination with mental accounting (Grinblatt and Han (2005)). Another is based on the realization utility (Barberis and Xiong (2012)).

pressure. As the demand by the risk-averse rational investors who accommodate the sell pressure is not perfectly elastic, prices are depressed, resulting in higher subsequent returns. Similarly, when a stock experiences bad news (a loser stock), and the stock price goes below the purchase price, disposition investors are reluctant to sell, causing loser stocks to earn lower subsequent returns. One natural way to vary liquidity in the Grinblatt and Han model is to increase the aggregate risk bearing capacity of the rational traders. This implies greater liquidity in the sense that the irrational net demand of the disposition traders has less effect on price. In consequence, lower illiquidity is associated with weaker momentum, which is inconsistent with our findings of a higher momentum in liquid markets.[4]

The paper is organized as follows. Section 2 presents a description of the characteristics of the momentum portfolios. In Section 3, we present evidence on the effect of market illiquidity and other state variables on momentum payoffs constructed from portfolio and individual security returns. Further analyses of the momentum-illiquidity relation using the recent sample period are provided in Section 4. Several robustness checks are presented in Section 5, followed by some concluding remarks in Section 6.

2. Data Description

The sample consists of all common stocks listed on NYSE, AMEX, and NASDAQ obtained from the Center for Research in Security Prices (CRSP), with a share code of 10 or 11. The sample spans the January 1928 through December 2011 period. Our portfolio formation method closely follows the approach in Daniel and Moskowitz (2012). Specifically, at the beginning of each month t, all common stocks are sorted into deciles based on their lagged eleven-month returns. Stock returns over the portfolio formation months, $t-12$ to $t-2$, are used to sort stocks into ten portfolios. The top (bottom) ten percent of stocks constitute the winner (loser) portfolios. The breakpoints for these

[4] Alternatively, illiquidity can be varied in the Grinblatt and Han (2005) model by varying simultaneously the risk-bearing capacity of both the rational and disposition traders, as reflected in the common parameter that determines the demand function of both types of traders in their model. This will vary the ability of both the rational and disposition traders to accommodate the trades by others (e.g., if exogenous random noise trading were added to the model), so that higher risk-bearing capacity is associated with lower price impact (i.e., higher liquidity). Varying this parameter has no effect on momentum in their model, so the implication is that varying liquidity has no effect on momentum, contrary to our empirical findings.

portfolios are based on returns of those stocks listed on NYSE only, so that the extreme portfolios are not dominated by the more volatile NASDAQ firms. The holding period returns for each stock is obtained after skipping month $t-1$, to avoid the short-term reversals reported in the literature (Jegadeesh (1990)). Finally, the portfolio holding period return in month t is the value-weighted average of stocks in each decile. Similar to Daniel and Moskowitz (2012), we require the stock to have valid share price and number of shares outstanding at the formation date, and at least eight valid monthly returns over the eleven-month formation period.

We first provide some summary statistics on the portfolios used in evaluating the momentum strategy. Panel A of Table 1 presents characteristics of these ten portfolios over the full sample period. The mean return in month t is increasing in past year returns and the winner portfolio outperforms the loser portfolio to generate a full-sample average winner-minus-loser (WML) portfolio return of 1.18 percent. Consistent with the existing literature, these profits are not due to exposure to common risk factors. For instance, the unconditional CAPM market beta of the loser portfolio (the short side of the momentum strategy) is in fact significantly larger than the beta for the winner portfolio by about 0.5. Consequently, the CAPM risk-adjusted WML portfolio return increases to 1.5 percent per month. Moreover, the WML returns are higher after adjusting for the Fama-French common risk factors – market (excess return on the value-weighted CRSP market index over the one-month T-bill rate), size (small minus big return premium (SMB)), and value (high book-to-market minus low book-to-market return premium (HML)).[5] The Fama-French three-factor risk-adjusted return for the WML portfolio is highly significant at 1.73 percent per month.

Table 1 also presents other characteristics of the portfolios. Several of these characteristics, including the Sharpe ratio and skewness of the portfolio returns, are similar to those reported in Daniel and Moskowitz (2012). For instance, the momentum profit (WML) is highly negatively skewed (skewness = -6.25), suggesting that momentum strategies come with occasional large crashes. Also reported are the cross-sectional differences in illiquidity across these portfolios. We employ the Amihud (2002) measure of stock illiquidity, $ILLIQ_{i,t}$, defined as $\left[\sum_{d=1}^{n}\left|R_{i,d}\right|/\left(P_{i,d}\times N_{i,d}\right)\right]/n$, where

[5] We thank Kenneth French for making the common factor returns available at this website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

n is the number of trading days in each month t, $|R_{i,d}|$ is the absolute value of return of stock i on day d, $P_{i,d}$ is the daily closing price of stock i, and $N_{i,d}$ is the number of shares of stock i traded during day d. The greater the change in stock price for a given trading volume, the higher would be the value of the Amihud illiquidity measure.

We find striking cross-sectional differences in the (value-weighted) average illiquidity of these portfolios. In particular, the loser (decile 1) portfolio contains the most illiquid stocks. The average $ILLIQ$ of the loser portfolio is 8.4, which is markedly higher compared to $ILLIQ$ of between 0.8 and 2.2 for the other nine portfolios. We explore the effect of cross-sectional differences in the average illiquidity of the loser and winner portfolios on the performance of the momentum strategy in Section 3.3.

In Panel B of Table 1, we compute measures of aggregate market liquidity and examine their time-series correlation with the WML returns. The level of market illiquidity in month $t-1$, $MKTILLIQ_{t-1}$, is defined as the value-weighted average of each stock's monthly Amihud illiquidity. Here, we restrict the sample to all NYSE/AMEX stocks as the reporting mechanism for trading volume differs between NYSE/AMEX and NASDAQ stock exchanges (Atkins and Dyl (1997)).[6] $MKTILLIQ_{t-1}$ is significantly negatively correlated with WML_t returns, with a correlation of −0.26, suggesting that momentum payoffs are low following periods of low aggregate liquidity. In unreported results, we consider an alternative measure that captures the innovations in aggregate market illiquidity, $INNOV\_MKTILLIQ_{t-1}$. It is obtained as the percentage change in $MKTILLIQ_{t-1}$ compared to the average of $MKTILLIQ$ over the previous two years ($t-24$ to $t-2$). Our results hold using this alternative market illiquidity measure. For example, we obtain a significant correlation of −0.12 between $INNOV\_MKTILLIQ_{t-1}$ and WML_t.

We also report the correlation between WML and two other aggregate variables that have been shown to predict the time variation in momentum payoffs. First, Cooper, Gutierrez, and Hameed (2004) show that the performance of the market index over the previous two years predicts

[6] Our measure, $MKTILLIQ$, proxies for aggregate market illiquidity, rather than illiquidity of a specific stock exchange. This is corroborated by the strong correlation between $MKTILLIQ$ and the aggregate illiquidity constructed using only NASDAQ stocks (the correlation is 0.78).

momentum payoffs, with profits confined to positive market return states. We compute the cumulative returns on the value-weighted market portfolio over the past 24 months (i.e., months $t-24$ to $t-1$), and denote the negative market returns by a dummy variable ($DOWN_{t-1}$) that takes the value of one only if a negative cumulative two-year return is recorded in month $t-1$. Consistent with Cooper, Gutierrez, and Hameed (2004), we find that $DOWN$ market states are associated with lower momentum profits. The correlation between the two variables is −0.13.

Wang and Xu (2010) document that, in addition to $DOWN$ market states, the aggregate market volatility significantly predicts momentum profits. Specifically, they find that the momentum strategy pays off poorly following periods of high market volatility. We use the standard deviation of daily value-weighted CRSP market index returns over the month $t-1$ as our measure of aggregate market volatility, $MKTVOL_{t-1}$. Indeed, the evidence suggests a significant negative correlation between $MKTVOL_{t-1}$ and WML_t (−0.12), confirming the findings in Wang and Xu (2010).

Moreover, as we show in Panel B, all three aggregate market level variables ($MKTILLIQ$, $DOWN$, and $MKTVOL$) are reasonably correlated, with correlations ranging from 0.33 to 0.42. While the univariate correlation between WML_t and $MKTILLIQ_{t-1}$ is supportive of a significant role for aggregate liquidity, it is important to evaluate the relative predictive power of the three dimensions of market conditions. Indeed, we will show in our analysis that the market illiquidity appears to be the strongest predictor of momentum profitability.

In Panel C of Table 1, we report the autocorrelation coefficient of the three state variables. All three variables are strongly persistent, although the autocorrelation is far smaller than 1.0. (For perspective, the aggregate dividend yield, the term spread, and the default spread display an autocorrelation coefficient of about 0.99.) Such autocorrelation could result in a small sample bias in predictive regressions (Stambaugh (1999)). Our results are robust to augmentation of the regression estimates for serial correlations in the explanatory variables prescribed in Amihud and Hurvich (2004).

3. Time Variation in Momentum Payoffs

3.1 Price Momentum in Portfolio Returns

In this section, we examine the predictive role of market illiquidity in explaining the inter-temporal variation in momentum payoffs, controlling for market volatility and market return states. Our examination is based on the following time-series regression specification:

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t \quad (1)$$

More precisely, we consider all eight combinations of the predictive variables, starting from the IID model which drops all predictors and retains the intercept only, ending with the all-inclusive model, which retains all predictors. In all these regressions, the dependent variable WML_t is the value-weighted return on the winner minus loser momentum deciles, formed based on the stock returns from months $t-12$ to $t-2$, as explained earlier.

The predictive variables include three aggregate measures of the market conditions in the prior month: $MKTILLIQ$, the level of market illiquidity, $DOWN$, the state of market return, and $MKTVOL$, the aggregate market volatility. The vector F stands for the Fama-French three factors, including the market factor, the size factor, and the book-to-market factor. The regression model gauges the ability of the three market state variables to predict the risk-adjusted returns on the momentum portfolio. We also run predictive regressions excluding the Fama-French risk factors and obtain similar results (which are not reported to conserve space).

The estimates of the eight regression specifications are reported in Panel A of Table 2. The evidence uniformly suggests a negative effect of aggregate market illiquidity on momentum profits. The slope coefficients of the market illiquidity measure are negative across the board, ranging from −0.253 (t-value = −2.41) for the all-inclusive specification (Model 8) to −0.35 (t-value = −4.28) for the illiquidity-only predictive model (Model 2).

Consistent with Cooper, Gutierrez, and Hameed (2004) and Wang and Xu (2010), we also find that momentum payoffs are lower in $DOWN$ market states and when market volatility ($MKTVOL$) is high. For instance, focusing on the predictive model that retains only $DOWN$ ($MKTVOL$), the slope coefficient is −2.405 (−1.592) recording t-value of −3.44 (−3.23). Panel A of Table 2 also shows that the inclusion of $MKTILLIQ$ weakens the predictive influence of $DOWN$ and $MKTVOL$ on WML. To illustrate, consider Model 8 which is an all-inclusive specification. While market illiquidity is statistically significant at conventional levels, market volatility is insignificant and the market states variable is significant only at the 10% level. Further, a one standard deviation increase in market illiquidity reduces the momentum profits by 0.87% per month, which is economically significant compared to the average monthly momentum profits 1.18% during the entire sample.[7] Indeed, the evidence arising from Table 2 confirms the important predictive role of market illiquidity on a stand-alone basis as well as on a joint basis.[8]

We consider the same eight regression specifications using the winner and loser payoffs separately as the dependent variables. In particular, we regress excess returns on the value-weighted loser and winner portfolios separately on the same set of predictive variables and the results are presented in Panels B and C of Table 2. The evidence here is consistent with that reported for the WML spread portfolio. To illustrate, the coefficient on $MKTILLIQ$ for loser stocks ranges between 0.133 and 0.199, while the corresponding figures for winner stocks are −0.12 and −0.151, all of which are significant. That is, the continuation in the loser and winner portfolios declines significantly following periods of high market illiquidity, with a slightly stronger effect on past losers. Again, the effect of $MKTILLIQ$ is not being challenged by the variation in either $DOWN$ or $MKTVOL$. Conversely, the predictive power of market return states and market volatility weakens considerably, often disappears, in the presence of market illiquidity (for example, see Panel C, Model 8).

In sum, the predictive effect of market illiquidity on momentum profits is robust. It remains significant after adjusting for the previously documented effects of down market and market volatility (Cooper, Gutierrez, and Hameed (2004), Wang and Xu (2010), and Daniel and Moskowitz (2012)).

3.2 Price Momentum in Individual Securities

Past work shows that there is significant gain as the testing ground shifts from portfolios to individual securities. Lo and MacKinlay (1990) argue that to avoid the data snooping bias it is preferable to implement asset pricing tests using individual securities rather than portfolios.

[7] The economic impact for $MKTILLIQ$ is quantified as $-0.253\% \times 3.454 = -0.87\%$, where -0.253% is the regression parameter of $MKTILLIQ$ on monthly momentum profits and 3.454 is the standard deviation of $MKTILLIQ$.
[8] Running the regression using $INNOV\_MKTILLIQ$ reveals that innovation in market illiquidity continues to be significant at conventional levels.

Litzenberger and Ramaswamy (1979) argue that valuable firm-specific information is lost with the aggregation to portfolios. Avramov and Chordia (2006) use returns on individual securities in a conditional beta asset-pricing setup to show new insights on the validity of various pricing models to account for market anomalies. For example, they find that the impact of momentum on the cross-section of individual stock returns are influenced by business cycle related variation in security risk and especially asset mispricing.

In our context, expanding the analysis to individual stocks is also useful as the WML portfolio considers only the extreme winner and loser stocks. We propose a two-stage analysis here. The first stage entails monthly cross-sectional regression specifications at the firm level, where the dependent variable is future one month return on stock i, $R_{i,t}$. The explanatory variables include the cumulative stock return in the formation period from months $t-12$ to $t-2$, $R_{i,t-12:t-2}$, as well as the lagged firm characteristics: Amihud stock level illiquidity measure, $ILLIQ_{i,t-1}$, firm size, $SIZE_{i,t-1}$, and the book-to-market ratio, $BM_{i,t-1}$. Excluding one or more of these firm characteristics in the regressions do not change our results. The monthly cross-sectional specifications take the form:

$$R_{i,t} = \alpha_0 + \beta_{0t}\, R_{i,t-12:t-2} + \gamma_{1t}\, ILLIQ_{i,t-1} + \gamma_{2t}\, SIZE_{i,t-1} + \gamma_{3t}\, BM_{i,t-1} + e_{i,t} \qquad (2)$$

The regression in Equation (2) is estimated each month so that the coefficient β_{0t} measures the security level momentum in month t for stock returns.

The second stage considers time-series regressions of β_{0t} on lagged market illiquidity, $DOWN$ market states, and market volatility. The empirical analysis excludes NASDAQ stocks to make sure that the trading volume-related Amihud (2002) illiquidity is comparable across stocks. The time-series regressions are formulated as

$$\beta_{0t} = \alpha_0 + \gamma_1 MKTILLIQ_{t-1} + \gamma_2 DOWN_{t-1} + \gamma_3 MKTVOL_{t-1} + e_t \qquad (3)$$

The time-series averages of the first-stage cross-sectional regression coefficients in Equation (2) are reported in Panel A of Table 3. The results provide individual security level evidence of a strong continuation in stock returns in the cross-section, i.e., β_{0t} is positive and highly significant. It should be noted that the individual stock momentum estimate accounts for the known effects of firm size, illiquidity and book-to-market on stock returns. As expected, the slope coefficient of the illiquidity control variable is significantly positive, consistent with illiquid stocks earning higher future returns than liquid stocks (Amihud (2002)).

Next, in Panel B of Table 3, we estimate the time-series regressions of the momentum coefficient β_{0t} on various collections of the three state variables, as in Equation (3). When the state variables $DOWN$ and $MKTVOL$ enter individually (Models 2 and 3), they significantly predict lower momentum in the following month. However, the predictive ability of the $DOWN$ market state and $MKTVOL$ vanishes in the presence of market illiquidity, as presented in Model 8. In contrast, in all model specifications, the level of market illiquidity displays a robust negative effect on momentum in individual securities.

The similarity in the effect of $MKTILLIQ$ on momentum in portfolio returns (Table 2) and individual stock returns (Table 3) lends credence to the proposition that the momentum payoffs become weak when the aggregate market is illiquid. Although $DOWN$ market return states and high $MKTVOL$ period may indirectly indicate low market liquidity, the aggregate market illiquidity displays a strong direct effect. Moreover, in the presence of the market illiquidity measure, the predictive power of $DOWN$ market and market volatility is attenuated.

3.3 Momentum and the Illiquidity Gap

The evidence thus far indicates that the momentum strategy is unprofitable when the aggregate market is illiquid. While loser stocks are generally more illiquid than winner stocks (as shown in Table 1), we raise the question of whether the differential performance of winners and losers depend on their relative illiquidity. When loser stocks become more illiquid than winner stocks, the losers are expected to earn higher future returns to compensate for the difference in illiquidity. Since the momentum strategy goes long on winners (less illiquid stocks) and short on losers (more illiquid stocks), the momentum strategy is likely to generate lower payoffs in times when the cross-sectional difference in illiquidity between the loser and winner portfolio is large. Moreover, the cross-sectional differences in illiquidity are expected to matter most when the aggregate market is highly illiquid.

To investigate if the cross-sectional differences in illiquidity affect the momentum payoffs, we introduce the notion of an illiquidity gap, defined as follows:

$$ILLIQGAP_{t-1} = ILLIQ_{WINNER,t-1} - ILLIQ_{LOSER,t-1} \quad (4)$$

where $ILLIQ_{WINNER,t-1}$ ($ILLIQ_{LOSER,t-1}$) is the average of the stock level Amihud (2002) illiquidity measure of all stocks in the winner (loser) decile during the momentum portfolio formation period (months $t-12$ to $t-2$). The level of $ILLIQGAP_{t-1}$ is mostly negative since the loser portfolio is unconditionally more illiquid than the winner portfolio. We examine whether momentum payoffs are significantly lower following periods when the loser portfolio is relatively more illiquid than winners. To pursue the task, the regression in Equation (1) is estimated with $ILLIQGAP_{t-1}$ as an additional explanatory variable. Since Amihud illiquidity is not comparable across NYSE/AMEX and NASDAQ stocks, we restrict the sample to firms listed on NYSE/AMEX only.

The results are reported in Table 4. Starting with Model 2, $ILLIQGAP_{t-1}$ predicts significantly lower momentum profits when the loser portfolio is more illiquid than the winner portfolio. Model 3 shows that the predictive effect of $ILLIQGAP_{t-1}$ is incremental to the prediction that illiquid market states produce lower momentum payoffs.

We note that the contemporaneous correlation between $ILLIQGAP_{t-1}$ and $MKTILLIQ_{t-1}$ is −0.14, implying that the illiquidity gap between the winners and losers is more negative as the market becomes more illiquid. The interaction of these two variables is highly significant, as depicted in Model 6. The latter findings emphasize that the gap in the liquidity between losers and winner has the biggest impact on expected momentum profits when the aggregate market is most illiquid.

Our findings in Table 4 highlight the nature of the relation between price momentum and illiquidity. When the stock market is liquid, the positive future return attributable to the (more illiquid) loser portfolio attenuates but does not eliminate the positive momentum payoffs. In illiquid periods, however, there are two reinforcing effects. First, high aggregate market illiquidity lowers the momentum in stock prices. Second, the illiquidity gap between the losers and winners widens, and the corresponding higher returns associated with illiquid stocks lowers momentum payoffs, and in some extreme scenarios, leads to negative momentum profits.

3.4 Momentum in Large Firms

The evidence of momentum in stock prices is pervasive and significant profits are present in stocks sorted by firm size. For example, Fama and French (2008) find that the momentum strategy yields significant returns in big, small, as well as micro-cap stocks, although small and micro-cap stocks are more likely to dominate portfolios sorted by extreme (winner/loser) returns. They argue that it is important to show that the phenomenon is systemic and is not concentrated in a group of small, illiquid stocks that make up a small portion of total market capitalization.

In this sub-section, we examine whether the time variation in expected momentum payoffs among the sample of large firms is captured by market illiquidity. Following Fama and French (2008), the sample here consists of firms with market capitalization above the median for NYSE firms each month. We also filter out firms with stock price below $5 each month.

The estimates of Equation (1) for the subset of large firms are presented in Table 5. Consistent with prior evidence, we continue to find significant (risk-adjusted) momentum profits of 1.57 percent in Model 1. More importantly, the state of market illiquidity, $MKTILLIQ$, predicts significantly lower returns to the momentum strategy applied to big firms. The slope coefficient ranges between −0.25 (t-value = −2.37) for Model 8 and −0.315 (t-value = −3.45) for Model 2. In addition, the other state variables, $DOWN$ and $MKTVOL$, also forecast lower profits. Interestingly, $MKTILLIQ$ also stands out as the strongest predictor in the sub-sample of large firms in all specifications, emphasizing our main contention that the effect of the state of market illiquidity is robust.

4. Evidence from Recent Period (2001−2011)

While most of the research papers on the profitability of momentum strategies employ data before 2000, Chordia, Subrahmanyam, and Tong (2014) show that price and earnings momentum payoffs are insignificant in the post-decimalization period, starting in April 2001. While the evidence in Chordia, Subrahmanyam, and Tong (2014) is unconditional, the main focus of our paper is on the time-varying nature of momentum payoffs. Indeed, improvements in market-wide liquidity in the recent decade due to technological and structural changes in the infrastructure have largely minimized the constraints to arbitrage, and hence provide an interesting setting to perform our analysis.

4.1 Price and Earnings Momentum

In addition to the price momentum strategies explored in Section 3, we also analyze earnings momentum. Trading strategies that exploit the post earnings announcement drift effect have been shown to be profitable (e.g., Ball and Brown (1968), Bernard and Thomas (1989), Chan, Jegadeesh, and Lakonishok (1996), and Chordia and Shivakumar (2006)). The data for our earnings momentum strategies come from analyst (consensus) earnings forecasts in I/B/E/S while the actual earnings are gathered from COMPUSTAT. The earnings announcement dates are obtained from I/B/E/S and COMPUSTAT following the procedure outlined by DellaVigna and Pollet (2009).

We follow Chan, Jegadeesh, and Lakonishok (1996) for our measures of earnings surprise, namely changes in analysts' earnings forecasts, standardized unexpected earnings, and cumulative abnormal returns around earnings announcements. The earnings momentum strategy is similar to the price momentum strategy except for ranking by earnings news. Specifically, at the beginning of each month t, all common stocks are sorted into deciles based on their lagged earnings news at $t-2$. The top (bottom) ten percent of stocks in terms of earnings surprise constitute the winner (loser) portfolio. The earnings momentum portfolio consists of a long position in the winner decile portfolio (extreme positive earnings surprise stocks) and a short position in loser decile portfolio (extreme negative earnings surprise stocks). The strategy's holding period return in month t is the value-weighted average of returns on stocks in the extreme deciles.

Our first measure of earnings surprise, which is based on the changes in analysts' forecasts of earnings (REV), is defined as

$$REV_{it} = \sum_{j=0}^{6} \frac{f_{it-j} - f_{it-j-1}}{P_{it-j-1}} \tag{5}$$

where f_{it-j} is the mean (consensus) estimate of firm i's earnings in month $t-j$ for the current fiscal year, and P_{it-j-1} is the stock price in the previous month (see also Givoly and Lakonishok (1979) and Stickel (1991)). The earnings surprise measure, REV_{it}, provides an up-to-date measure at the monthly frequency since analyst forecasts are available on a monthly basis and it has the advantage of not requiring estimates of expected earnings.

An alternative measure of earnings surprise is the standardized unexpected earnings (SUE), defined as

$$SUE_{it} = \frac{e_{iq} - e_{iq-4}}{\sigma_{it}} \tag{6}$$

where e_{iq} is the most recent quarterly earnings per share for stock i announced as of month t, e_{iq-4} is the earnings per share announced four quarters ago, and σ_{it} is the standard deviation of unexpected earnings ($e_{iq} - e_{iq-4}$) over the previous eight quarters. While SUE_{it} is commonly used in the literature (see also Bernard and Thomas (1989), Foster, Olsen, and Shevlin (1984) and Chordia and Shivakumar (2006)), this earnings surprise measure is not updated for stock i in month t if the firm did not announce its earnings.

Finally, we also compute earnings surprise using the cumulative abnormal stock return (CAR) around the earnings announcement dates, where the stock i's return is in excess of the return on the market portfolio. Specifically, CAR_{it} for stock i in month t is computed from day −2 to day +1, with day 0 defined by the earnings announcement date in month t,

$$CAR_{it} = \sum_{d=-2}^{+1} (r_{id} - r_{md}) \tag{7}$$

where r_{id} is the return on stock i in day d, and r_{md} is the return on the CRSP equally weighted market portfolio. When measuring earnings surprise with SUE_{it} or CAR_{it}, we retain the same earnings surprise figures between reporting months.

We begin with the presentation of estimates of the regression in Equation (1) for the price momentum portfolio during the recent period from April 2001 to December 2011. Consistent with Chordia, Subrahmanyam, and Tong (2014), the risk-adjusted price momentum profit in Panel A of Table 6 is insignificant at 0.24 percent.[9] Figure 1 plots the payoffs to the price momentum and the value of the state variables. The figure suggests that the lack of profitability of price momentum in the recent decade is possibly related to periodic episodes of market illiquidity, since low momentum payoff months seem to coincide with periods of high lagged market illiquidity. In support of this

[9] The raw price momentum returns in 2001−2011 are also insignificant at 0.18 percent per month.

assertion, controlling for the significant (negative) effect of $MKTILLIQ$ on WML generates significant momentum profits, as indicated by the intercept in Model 2 of Panel A, Table 6. To gauge the economic magnitude of the effect of $MKTILLIQ$ states, we compute WML in illiquid (liquid) sub-periods defined as those months with above (below) the median value of $MKTILLIQ$ in the 2001−2011 sample. There is a marked increase in WML, from −0.69 percent (t-value = −0.50) when the market is illiquid to 1.09 percent (t-value = 2.20) per month in liquid market states.

Additionally, we obtain similar evidence that months following $DOWN$ markets and high market volatility are associated with significantly lower momentum profits. However, the predictive power of $DOWN$ and $MKTVOL$ disappears in the presence of $MKTILLIQ$. Indeed, Models 5 to 8 in Panel A complements the cumulative results we have presented thus far: the state of market illiquidity dominantly governs the (lack of) profitability of price momentum strategies.

Panels B to D in Table 6 lay the results based on earnings momentum. In Panel B, the momentum portfolios use earnings surprise based on the revision in analyst forecasts of earnings (REV). As shown by estimate of Model 1 in Panel B of Table 6, we obtain a significant earnings momentum profit of 1.12 percent per month, after adjusting for the Fama-French risk factors. Unlike the disappearance of price momentum, significant earnings momentum is recorded even in the most recent years. Nevertheless, the earnings momentum profits plotted in Figure 1 displays a high correlation with the lagged market illiquidity, similar to the payoffs from the price momentum strategy. This observation is confirmed in the regressions of earnings momentum profits on each of the state variables.

Earnings momentum profitability is significantly lower following illiquid aggregate market ($MKTILLIQ$) states (Model 2) and $DOWN$ markets (Model 3). Market volatility, $MKTVOL$, on the other hand, does not appear to have any significant predictive effects on earnings momentum on its own (Model 4). More importantly, $MKTILLIQ$ retains its significance in the presence of two or more state variables, across all specifications in Models 5, 6 and 8.

When earnings surprise at the firm level is measured by changes in its standardized unexpected earnings (SUE), we find that only $MKTILLIQ$ enters significantly when the predictive regression is estimated with only one explanatory variable (Model 2). As displayed in Panel C of Table 6 (Models 3 and 4), $DOWN$ and $MKTVOL$ are insignificant predictors of earnings momentum. When all the state variables are considered together, only the state of market illiquidity is able to significantly capture a drop in earnings momentum in the following month (Model 8).

Finally, in Panel D of Table 6 the earnings surprise is constructed using the abnormal stock price reactions in the announcement month t (CAR). Interestingly, the average risk-adjusted earnings momentum profit using stocks sorted on CAR is not positive in the last decade, yielding an insignificant -0.17 percent per month (Model 1). Controlling for the negative effect of $DOWN$ market states on momentum, the payoff to the earnings momentum regains a significant positive value of 0.5 percent following a rise in aggregate market valuations (Model 3). In addition, $MKTILLIQ$ (Model 2) and $MKTVOL$ (Model 4) also significantly predict future earnings momentum profits when they are the only single state variable in the regression specification. However, in an all-inclusive specification (Model 8) $MKTILLIQ$ stands out as the only significant predictor.

In summary, the analysis of price and earnings momentum in the recent decade complements the cumulative evidence we have presented: the state of market illiquidity is a dominant predictor of the profitability of momentum strategies.

4.2 Do Investor Sentiment and Macroeconomic Conditions Explain the Market Illiquidity Effect?

Investor sentiment has been shown to affect the returns associated with a broad set of market anomalies. For example, Stambaugh, Yu, and Yuan (2012) show that various cross-sectional anomalies, including price momentum, are profitable during periods of high investor sentiment. In particular, profitability of these long-short strategies stems from the short-leg of the strategies, reflecting binding short-sale constraints following high sentiment. Antoniou, Doukas, and Subrahmanyam (2013) also report that momentum strategies are not profitable when investor sentiment is pessimistic. We examine whether the market illiquidity effects simply reflect the influence of investor sentiment on momentum profits.

We run various predictive regressions with different combinations of the predictive state variables as well as measures of investor sentiment. We consider two alternative definitions of the sentiment variable. The first is the level of sentiment index obtained from Baker and Wurgler (2006, 2007).[10] The second is a low sentiment dummy variable that takes a value of one only if the sentiment index value belongs to the bottom tercile over the sample period, 2001−2011. The results presented in Table 7 show that sentiment has a positive effect on momentum profits as low sentiment periods display low momentum payoffs (Model 1), similar to the findings in the above cited papers. Of special interest to our analysis is that $MKTILLIQ$ is highly significant in the presence of sentiment indicators in Models 2 and 3 (i.e., using either low sentiment dummy and the level of investor sentiment index), indicating that our findings are not subsumed by the two investor sentiment variables.

In unreported results, we consider an alternative approach of sorting the sample months from 2001 to 2010 into three equal groups based on the level of aggregate market illiquidity in month $t-1$, $MKTILLIQ_{t-1}$. Within each of the three $MKTILLIQ_{t-1}$ terciles, the observations are further sorted into High, Medium, and Low sentiment in month $t-1$ (using Baker-Wurgler sentiment index) to generate nine sub-periods. When the equity market is illiquid, we find that momentum is unprofitable in all sentiment states, including the most optimistic state. Moreover, the WML portfolio displays negative payoffs when sentiment is High but the market is illiquid. These results confirm that the variation in momentum profits associated with state of market illiquidity is not explained by the investor sentiment.

Naes, Skjeltorp, and Odegaard (2011) show that the aggregate stock market illiquidity is counter-cyclical and significantly predicts the real economy. Chordia and Shivakumar (2002; henceforth, CS) argue that the profits to momentum strategies are explained by common macroeconomic variables and are related to the business cycle. Specifically, CS find that the momentum profits are strong (weak) in expansionary (recessionary) periods. Taken together, these findings imply that the profitability of the momentum strategies could be due to variations in the common macroeconomic factors, and presumably changes in risks. We examine if the negative association we find between market illiquidity and momentum can be explained by variations in the macroeconomy as suggested in CS.

[10] We thank Jeffry Wurgler for making their index of investor sentiment publicly available.

Following CS, we use dividend yield, yield on three-month T-bills, default and term spreads as our macroeconomic variables. We add the lagged values of these variables to the time-series regression models in Equation (1). As shown in Model 4 of Table 7, adding these macroeconomic variables does not attenuate the strong negative influence of market illiquidity.

Stivers and Sun (2010) use the cross-sectional dispersion in stock returns ($CSRD$) as a countercyclical state variable to explain time variation in momentum profits. Stivers and Sun find that the high *CSRD* coincides with economic recessions and significantly predicts lower momentum payoffs, after controlling for the macroeconomic variables in CS. Following Stivers and Sun (2010), *CSRD* is the three-month moving average of the monthly cross-sectional return dispersion, constructed from 10×10 stock portfolios formed on firm size and book-to-market ratio. Specifically, *CSRD* is computed over months $t-3$ to $t-1$ to predict WML in month t. In Model 5 of Table 7, we report that *CSRD* is a significant predictor of momentum payoffs, consistent with Stivers and Sun (2010). However, when we include both $MKTILLIQ$ and $CSRD$, the state of the market liquidity remains significant, as shown in Model 6.

In Model 7 of Table 7, we report a joint regression model which includes $DOWN$ market state, market volatility, investor sentiment, cross-sectional return dispersion and the Fama-French three risk factors. Again, the state of market liquidity makes a significant contribution in determining future momentum payoffs. In a recent paper, Liu and Zhang (2008) suggest that macroeconomic risk factors in Chen, Roll, and Ross (1986), and in particular the growth rate of industrial production, explains a significant portion of momentum profits. We consider replacing the Fama-French risk factors with the Chen, Roll, and Ross's five macroeconomic factors, which are the growth rate of industrial production, unexpected inflation, change in expected inflation, term and default premiums. Adjusting for these risk factors, which are contemporaneous with the momentum profits, do not alter the findings on negative impact of market illiquidity state on subsequent momentum payoffs (Model 8, Table 7). Our findings reinforce the results in Liu and Zhang (2014): their real investment model of asset prices does not generate the time variation in momentum profits that we observe in the data.

4.3 Liquidity Risk Effects

Our analysis of the effect of illiquidity level differs from the important work of Pastor and Stambaugh (2003), Sadka (2006) and Assness, Moskowitz, and Pedersen (2013) − all of which examine the liquidity risk (beta) exposure of the momentum strategies. Their investigations show that the momentum portfolio has significant exposure to variations in the systematic liquidity factor, which in turn, explains some, albeit small, portion of momentum payoffs. In this sub-section, we examine if the momentum-illiquidity relation is explained by variations in their liquidity risk exposures.

For a start, we add the Pastor-Stambaugh liquidity factor in the regressions along with the three Fama-French factors. Consistent with prior literature, the results in Table 7 shows that the momentum portfolio loads significantly on the liquidity factor. However, the predictive effect of $MKTILLIQ$ on momentum profits is unabated across various specifications of the four-factor model (see Models 9 and 10 in Table 7).[11]

Additionally, we construct the momentum portfolio which is liquidity risk neutral. Specifically, at the beginning of each month t, the liquidity beta is estimated for each NYSE/AMEX stock based on a four-factor model estimated over the previous (rolling) sixty months, where the factors are the Fama-French three factors and the Pastor-Stambaugh liquidity factor. The stocks are then sorted into quintiles depending on their liquidity beta. Within each liquidity beta group, we compute the (value-weighted) returns of the winner and loser deciles, which are defined according to their formation period returns from months $t-12$ to $t-2$. The overall loser (winner) portfolio return is the equal-weighted average of all the bottom (top) decile portfolios across all liquidity-beta quintiles. The resulting liquidity-beta neutral momentum portfolio returns are regressed on the four factors as well as $MKTILLIQ$ and other state variables. In unreported results (available upon request), we find that the state of market illiquidity continues to have a significant predictive effect on momentum profits. These results show that the effect of market liquidity on momentum payoffs is different from the liquidity risk exposure of the momentum portfolio.

[11] We get similar results when we control for any predictive effect of other variables that may proxy for funding liquidity, including the TED spread and VIX (the implied volatility of the S&P 500 index options) in Assness, Moskowitz, and Pederson (2013).

5. Other Robustness Checks

5.1 Alternative Measure of Aggregate Market Illiquidity

We consider an alternative measure of liquidity introduced recently by Corwin and Schultz (2012). Corwin and Schultz estimate the bid-ask spreads (or the cost of trading) using only daily high and low stock prices. They show that their spread estimator is highly correlated with high frequency measures of bid-ask spreads in both time-series and cross-sectional analysis, has similar power to the Amihud (2002) illiquidity measure, and outperforms several other low frequency estimators of liquidity. Specifically, the monthly Corwin-Schultz spread estimator ($Spread$) for each stock is computed based on the high-to-low price ratio for a single two-day period and the high-to-low ratio over two consecutive single days.[12] The value-weighted average of $Spread$ across all stocks in the market, $MKTSPREAD$, is our alternative measure of the state of aggregate market illiquidity. As expected, $MKTSPREAD$ is correlated (but not perfectly) with $MKTILLIQ$, with a correlation coefficient of 0.57 over the period 1928 to 2011.

In the analysis that follows, we re-estimate Equation (1), replacing $MKTILLIQ$ with $MKTSPREAD$ and present the estimates in Table 8. The overall results confirm our main findings that momentum payoffs are low when the aggregate market is highly illiquid. For example, Model 1 shows that a one standard deviation increase in $MKTSPREAD$ reduces the risk-adjusted monthly momentum profits by an economically significant 1.17 percent. Similar to our findings in Table 2, Models 2 to 4 in Table 8 shows that adding the other state variables ($DOWN$ and $MKTVOL$) does not fully explain the strong negative effect of market-wide illiquidity on the returns to the momentum strategy. Hence, our finding on the momentum-illiquidity relation is robust to alternate measures of market illiquidity.

5.2 International Evidence

[12] The Corwin-Schultz (2012) spread estimator is given by $Spread = \frac{2(e^{\alpha}-1)}{1+e^{\alpha}}$, where $\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$; $\beta = E\left\{\sum_{j=0}^{1}\left[ln\frac{H_{t+j}}{L_{t+j}}\right]^2\right\}$ and $\gamma = \left[ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2$. In these notations, H_t (L_t) refers to the observed high (low) stock price in day t and negative two-day spreads are set to zero.

We also examine the time-variation of momentum profits in an international sample. Our non-US sample, which spans the 2001 to 2010 period, consists of Japan and the set of ten countries that belongs to the Eurozone at the beginning of our sample period, including Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, and Spain. We obtain price and volume data for all common stocks traded on the primary exchange in each country from Datastream. After converting all prices to US dollars, we exclude stocks with extreme prices, that is, those below US$1 or above US$1000 to minimize microstructure biases and potential data errors.

The methodology for computing the main variables in our analyses are similar to those described in Section 2. Within each country, we form winner and loser decile portfolios based on the stock returns over the previous eleven months, from $t-12$ to $t-2$. The WML portfolio returns are computed each month as the difference in the returns of the value-weighted winner and loser decile portfolios in month $t+1$. For the Eurozone sample, we form country-neutral value-weighted WML portfolio returns based on the combined sample of all stocks in the ten countries. For Japan, the state variables,$MKTILLIQ$, $DOWN$, and $MKTVOL$, are based on the value-weighted average of all stocks traded on the Tokyo Stock Exchange. The corresponding value of the state variables for the Eurozone stock market reflect the value-weighted average of all stocks traded in the ten markets. Finally, the Fama-French three common risk factors (market, size, and value) for Japan and the European market are downloaded from Ken French's website.

The estimate of Equation (1) for Japan is presented in Panel A of Table 9. As documented in recent papers, Model 1 shows that, unconditionally, momentum strategies do not work in the Japanese market. Chui, Titman, and Wei (2010), for example, argue that investors in less individualistic cultures, such as Japan, exhibit smaller overconfident/self-attribution bias, and hence, there is no evidence of price momentum in these markets. However, conditioning the time-series of momentum payoffs on $MKTILLIQ$, leads to significant momentum profits (see Model 2). In other words, we find significant momentum even in the Japanese stocks when aggregate illiquidity is low. Similar to our findings for the US market, $MKTILLIQ$ as an aggregate variable has the greatest influence on momentum payoffs in Japan as well. The $DOWN$ state predicts momentum payoffs on a stand-alone basis (Model 3), but loses its significance in the presence of $MKTILLIQ$ (Models 5 and 8). The time variation in $MKTVOL$, on the other hand, is not related to (the absence of) momentum in Japan.

The results for the Eurozone market is reported in Table 9, Panel B. Similar to the results for Japan and the post 2000 sample in the US, we do not find evidence of significant unconditional momentum in the Eurozone market. However, momentum emerges to a significant phenomenon when we condition on the state variables: momentum is positive and significant, except in bad times ─ after decreases in aggregate market valuations ($DOWN$), when markets are volatile ($MKTVOL$), and, especially, when the market is illiquid ($MKTILLIQ$). Of these three state variables, $MKTILLIQ$ and $MKTVOL$ have the strongest effect on momentum payoffs.

The overwhelming evidence across the US, Japan, and Eurozone sample is that market illiquidity predicts momentum payoffs, and its impact is pervasive across all these markets.

6. Conclusion

In this paper, we examine the association between the variation in market liquidity and the momentum anomaly and provide a direct test of the role of liquidity for arbitrage. A basic intuition is that arbitrage of the momentum anomaly is easier when markets are most liquid. If variations in momentum profits reflect changes in arbitrage constraints, we expect a positive relation between momentum profits and aggregate market liquidity. Surprisingly, we find that the effect goes in the opposite direction, and rather sharply. We find that the momentum strategy generates large (weak) profits when the market is highly liquid (illiquid), which contrasts with the arbitrage prediction.

The negative momentum-illiquidity relation is robust. In the presence of market illiquidity, the power of the competing variables that have been shown to predict variation in momentum profits, namely market return states and market volatility, is attenuated and often even disappears altogether. We obtain similar findings across different empirical approaches using returns on individual securities or portfolios and across alternative proxies for liquidity. Our results hold in a subset of large firms and also in the most recent decade wherein technological developments and improvements in the market infrastructure has lowered the barriers to arbitrage. For example, in the post-decimalization period (from 2001 to 2011), the monthly momentum profits increases dramatically from -0.69 percent when the market is illiquid to 1.09 percent during relatively liquid market states. We also find similar market illiquidity effects in stocks traded in Japan and Eurozone countries. Finally, we uncover that the same negative momentum-illiquidity relation governs the variation of the profits to the earnings momentum strategy.

We examine whether the negative momentum-illiquidity relation is subsumed by other known explanations. We investigate the possibility that the stock market illiquidity is an indicator of the state of the economy, as suggested by Naes, Skjeltorp, and Odegaard (2011), and that variation in momentum payoffs reflects time-varying expected returns over the business cycle (Chordia and Shivakumar (2002)). Our findings on the predictive effect of market illiquidity on momentum are unaffected when we control for the state of the macroeconomy and the cross-sectional dispersion in stock returns (Stivers and Sun (2010)). Additionally, we find that the effect of market liquidity is robust to, and partially subsumes the recent evidence that momentum payoffs depend on inter-temporal variation in investor sentiment, as documented by Stambaugh, Yu, and Yuan (2012) and Antoniou, Doukas, and Subrahmanyam (2013). Hence, market illiquidity does not simply reflect changing investor sentiment.

Our findings also complement the important studies on the liquidity risk (beta) exposure of the momentum portfolio (Pastor and Stambaugh (2003), and Assness, Moskowitz, and Pedersen (2013)). Controlling for liquidity risk (beta) exposures, we continue to find a significant negative loading of market illiquidity state on momentum payoffs. The momentum investment strategy buys winners (which tend to be liquid stocks) and sells losers (which tend to be illiquid stocks) and, hence, has an imbedded negative liquidity premium (Amihud (2002)). When market as a whole is illiquid, we find that the larger difference in the liquidity characteristics of the winner and loser stocks (or a large illiquidity gap) cause the loser portfolio to earn *high* subsequent return, or a considerably lower payoff to the momentum strategy.

Our findings also help to distinguish behavioral explanations of the momentum anomaly. We argue that our findings are consistent with (though they do not prove) market liquidity as an indicator of investor overconfidence, and where overconfidence in turn drives the variation in the momentum effect, implying an association between illiquidity and momentum. While we do not pin down the tests to a specific model (such as Daniel, Hirshleifer, and Subrahmanyam (1998)), the results support overconfidence as a source of momentum. On the other hand, we consider the idea that momentum is driven by underreaction to information due to the disposition effect as espoused by Grinblatt and Han (2005). However, Grinblatt and Han would predict that lower illiquidity is associated with weaker momentum, which is inconsistent with our findings.

References

Amihud, Y. 2002. Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets* 5:31−56.

Amihud, Y., and C. M. Hurvich. 2004. Predictive Regression: A Reduced-Bias Estimation Method. *Journal of Financial and Quantitative Analysis* 39:813–841.

Amihud, Y., and H. Mendelson. 1986. Asset Pricing and the Bid-Ask Spread. *Journal of Financial Economics* 17:223−249.

Antoniou, C., J. A. Doukas, and A. Subrahmanyam. 2013. Cognitive Dissonance, Sentiment and Momentum. *Journal of Financial and Quantitative Analysis* 48: 245–275.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. Value and Momentum Everywhere. *Journal of Finance* 68:929−985.

Atkins, A., and E. Dyl. 1997. Market Structure and Reported Trading Volume: NASDAQ Versus the NYSE. *Journal of Financial Research* 20:291−304.

Avramov, D., and T. Chordia. 2006. Asset Pricing Models and Financial Market Anomalies. *Review of Financial Studies* 19:1001–1040.

Ball, R., and P. Brown. 1968. An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research* 6:159–178.

Baker, M., and J. C. Stein. 2004. Market Liquidity as a Sentiment Indicator. *Journal of Financial Markets* 7:271–299.

Baker, M., and J. Wurgler. 2006. Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance* 61:1645–1680.

Baker, M., and J. Wurgler. 2007. Investor Sentiment in the Stock Market. *Journal of Economic Perspectives* 21:129−152.

Barberis, N., A. Shleifer, and R. Vishny. 1998. A Model of Investor Sentiment. *Journal of Financial Economics* 49:307–343.

Barberis, N., and W. Xiong. 2012. Realization Utility. *Journal of Financial Economics* 104:251−271.

Bernanrd, V., and J. Thomas. 1989. Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? *Journal of Accounting Research* 27:1−36.

Chan, L. K. C., N. Jegadeesh, and J. Lakonishok. 1996. Momentum Strategies. *Journal of Finance* 51:1681–1713.

Chen, N. F., R. Roll, and S. A. Ross. 1986. Economic Forces and the Stock Market. *Journal of Business* 59:383–403.

Chordia, T., and L. Shivakumar. 2002. Momentum, Business Cycle, and Time-varying Expected Returns. Journal of Finance 57: 985–1019.

Chordia, T., and L. Shivakumar. 2006. Earnings and Price Momentum. *Journal of Financial Economics* 80:627−656.

Chordia, T., A. Subrahmanyam, and Q. Tong. 2014. Have Capital Market Anomalies Attenuated in the Recent Era of High Liquidity and Trading Activity? *Journal of Accounting and Economics* 58:41−58.

Chui, A., S. Titman, and J. Wei. 2010. Individualism and Momentum around the World. *Journal of Finance*, 65:361–392.

Cooper, M. J., R. C. Gutierrez Jr., and A. Hameed. 2004. Market States and Momentum. *Journal of Finance* 59:1345–1365.

Corwin, S. and A., P. Schultz. 2012. A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices. *Journal of Finance* 67:719–759.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance* 53:1839–1885.

Daniel, K., and T. Moskowitz. 2012. Momentum Crashes. Working Paper.

DellaVigna, S., and J. M. Pollet. 2009. Investor Inattention and Friday Earnings Announcements. *Journal of Finance* 64:709–749.

Fama, E., and K. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33:3−56.

Fama, E., and K. French. 2008. Dissecting Anomalies. *Journal of Finance* 63:1653−1678.

Foster, G., C. Olsen, and T. Shevlin. 1984. Earnings Releases, Anomalies, and the Behavior of Security Returns. *The Accounting Review* 59:574–603.

Givoly, D., and J. Lakonishok. 1979. The Information Content of Financial Analysts' Forecasts of Earnings: Some Evidence on Semi-Strong Inefficiency. *Journal of Accounting and Economics* 1:165–185.

Griffin, J. M., X. Ji, and J. S. Martin. 2003. Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole. *Journal of Finance* 58:2515−2547.

Grinblatt, M., and B. Han. 2005. Prospect Theory, Mental Accounting, and Momentum. *Journal of Financial Economics* 78:311–339.

Hong, H., and J. C. Stein. 1999. A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *Journal of Finance* 54: 2143–2184.

Jegadeesh, N. 1990. Evidence of Predictable Behavior in Security Prices. *Journal of Finance* 45:881−898.

Jegadeesh, N., and S. Titman. 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance* 48:65−91.

Litzenburger, R., and K. Ramaswamy. 1979. The Effect of Personal Taxes and Dividends on Capital Asset Prices: Theory and Empirical Evidence. *Journal of Financial Economics* 7:163−195.

Liu, X., and L. Zhang. 2008. Momentum Profits, Factor Pricing, and Macroeconomic Risk. *Review of Financial Studies* 21:2417−2448.

Liu, X., and L. Zhang. 2014. A Neoclassical Interpretation of Momentum. *Journal of Monetary Economics* 67:109−128.

Lo, A. W., and A. C. MacKinlay. 1990. Data-Snooping Biases in Tests of Financial Asset Pricing Models. *Review of Financial Studies* 3:431−468.

Næs, R., J. A. Skjeltorp, and B. A. Ødegaard. 2011. Stock Market Liquidity and the Business Cycle. *Journal of Finance* 66:139−176.

Newey, W. K., and K. D. West. 1987. A Simple Positive-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55:703–708.

Odean, T. 1998. Volume, Volatility, Price, and Profit When All Traders Are Above Average. *Journal of Finance* 53:1887–1934.

Pástor, L., and R. F. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111:642–685.

Sadka, R. 2006. Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk. *Journal of Financial Economics* 80:309–349.

Stambaugh, R. F. 1999. Predictive Regressions. *Journal of Financial Economics* 54:375–421.

Stambaugh, R. F., J. Yu, and Y. Yuan. 2012. The Short of It: Investor Sentiment and Anomalies. *Journal of Financial Economics* 104:288−302.

Stickel, S. E. 1991. Common Stock Returns Surrounding Earnings Forecast Revisions: More Puzzling Evidence. *The Accounting Review* 66: 402–416.

Stivers, C., and L. Sun. 2010. Cross-Sectional Return Dispersion and Time Variation in Value and Momentum Premiums. *Journal of Financial and Quantitative Analysis* 45: 987–1014.

Wang, K. Q., and J. Xu. 2010. Time-Varying Momentum Profitability. Working Paper.

Table 1: Descriptive Statistics for Momentum Portfolios and Market States

Panel A presents characteristics of the monthly momentum portfolio in our sample during the period from 1928 to 2011. At the beginning of each month t, all common stocks listed on NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged eleven-month returns (formation period is from $t-12$ to $t-2$, skipping month $t-1$). The portfolio breakpoints are based on NYSE firms only. We report the average monthly value-weighted holding period (month t) returns of each decile portfolio, as well as the momentum profits (WML, winner minus loser deciles). The returns are further adjusted by CAPM and Fama-French three-factor model to obtain CAPM and 3-Factor Alphas. We also report the CAPM beta, return autocorrelation (AR(1)), standard deviation of return, Sharpe ratio, information ratio, skewness, and Amihud illiquidity (ILLIQ). Sharpe ratio (Information ratio) is computed as the average monthly excess portfolio return (CAPM alpha) divided by its standard deviation (portfolio tracking error) over the entire sample period. For all portfolios except WML, skewness refers to the realized skewness of the monthly log returns to the portfolios. For WML, skewness refers to the realized skewness of $\log(1+r_{WML}+r_f)$, following Daniel and Moskowitz (2012). Panel B reports the correlation of WML and market state variables, including the aggregate market illiquidity (MKTILLIQ), DOWN market dummy (for negative market returns over the previous 2 years), and market return volatility(MKTVOL).Panel C reports the autocorrelation of WML and market state variables. Newey-West adjusted t-statistics are reported in parentheses, and the numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Characteristics of Momentum Decile Portfolios											
	1 (Loser)	2	3	4	5	6	7	8	9	10 (Winner)	WML
Raw Return (in %)	0.291	0.698***	0.701***	0.833***	0.821***	0.909***	0.987***	1.102***	1.168***	1.470***	1.179***
	(0.95)	(2.89)	(3.17)	(3.94)	(4.58)	(4.82)	(5.39)	(5.94)	(5.88)	(6.67)	(4.84)
CAPM Alpha (in %)	-0.926***	-0.388***	-0.290***	-0.113	-0.084	0.006	0.118*	0.254***	0.299***	0.572***	1.497***
	(-6.26)	(-3.73)	(-3.15)	(-1.45)	(-1.26)	(0.12)	(1.96)	(5.05)	(4.49)	(5.67)	(8.17)
CAPM Beta	1.550***	1.332***	1.171***	1.097***	1.027***	1.024***	0.966***	0.931***	0.966***	1.015***	-0.535***
	(16.77)	(14.23)	(15.14)	(19.12)	(19.71)	(26.99)	(39.99)	(38.10)	(24.76)	(11.67)	(-3.05)
3-Factor Alpha (in %)	-1.105***	-0.524***	-0.386***	-0.186***	-0.145**	-0.039	0.110*	0.259***	0.317***	0.624***	1.730***
	(-8.71)	(-5.09)	(-4.08)	(-2.58)	(-2.45)	(-0.83)	(1.90)	(5.13)	(4.37)	(6.65)	(9.29)
AR(1)	0.165	0.148	0.124	0.123	0.104	0.107	0.058	0.091	0.055	0.068	0.085
Std.Dev.(Raw Return)	9.883	8.217	7.098	6.502	6.021	5.879	5.584	5.423	5.735	6.562	7.952
Sharpe Ratio	0.000	0.049	0.057	0.083	0.087	0.104	0.124	0.149	0.152	0.179	0.148
Information Ratio	-0.183	-0.103	-0.096	-0.046	-0.039	0.003	0.066	0.138	0.136	0.164	0.203
Skewness	0.143	-0.018	-0.086	0.214	-0.106	-0.265	-0.580	-0.529	-0.760	-0.905	-6.252
ILLIQ	8.387	3.625	1.864	1.163	1.180	1.038	0.827	0.586	0.781	2.170	-6.217

Table 1—Continued

Panel B: Correlation among Market States				
	WML	MKTILLIQ	DOWN	MKTVOL
WML	1.000			
MKTILLIQ	-0.258	1.000		
DOWN	-0.129	0.327	1.000	
MKTVOL	-0.122	0.396	0.422	1.000

Panel C: Autocorrelation of Market States				
	WML	MKTILLIQ	DOWN	MKTVOL
AR(1)	0.085	0.894***	0.875***	0.719***
	(1.01)	(22.05)	(28.80)	(14.82)

Table 2: Momentum Profits and Market States

Panel A presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t, $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). Panels B and C report similar regression parameters, where the dependent variable is the excess value-weighted portfolio return in loser and winner deciles, respectively. The sample period is from 1928 to 2011. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Momentum Profit (WML) Regressed on Lagged Market State Variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.730***	2.049***	2.169***	3.123***	2.284***	2.826***	3.035***	2.789***
	(9.29)	(9.57)	(10.50)	(6.86)	(11.44)	(6.49)	(6.97)	(6.62)
MKTILLIQ		-0.350***			-0.290***	-0.280***		-0.253**
		(-4.28)			(-3.05)	(-2.82)		(-2.41)
DOWN			-2.405***		-1.584**		-1.656***	-1.240*
			(-3.44)		(-1.96)		(-2.94)	(-1.87)
MKTVOL				-1.592***		-0.961*	-1.146**	-0.688
				(-3.23)		(-1.65)	(-2.55)	(-1.38)
RMRF	-0.387***	-0.373***	-0.393***	-0.391***	-0.380***	-0.378***	-0.394***	-0.382***
	(-3.42)	(-3.27)	(-3.37)	(-3.40)	(-3.27)	(-3.27)	(-3.38)	(-3.28)
SMB	-0.247*	-0.213	-0.224*	-0.231*	-0.204	-0.210	-0.219	-0.204
	(-1.80)	(-1.56)	(-1.67)	(-1.68)	(-1.52)	(-1.54)	(-1.62)	(-1.51)
HML	-0.665***	-0.599***	-0.659***	-0.667***	-0.606***	-0.613***	-0.662***	-0.615***
	(-3.57)	(-3.68)	(-3.62)	(-3.66)	(-3.68)	(-3.71)	(-3.67)	(-3.70)
Adj-Rsq	0.232	0.254	0.246	0.247	0.259	0.259	0.252	0.261

Table 2—Continued

Panel B: Excess Loser Portfolio Return Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-1.105***	-1.287***	-1.402***	-1.939***	-1.462***	-1.775***	-1.875***	-1.746***
	(-8.71)	(-8.98)	(-9.99)	(-6.26)	(-10.56)	(-5.68)	(-6.35)	(-5.81)
MKTILLIQ		0.199***			0.154**	0.154**		0.133*
		(4.08)			(2.51)	(2.45)		(1.93)
DOWN			1.621***		1.186**		1.211***	0.993**
			(3.14)		(1.99)		(2.76)	(1.98)
MKTVOL				0.952***		0.605	0.626*	0.386
				(2.64)		(1.41)	(1.93)	(1.06)
RMRF	1.390***	1.383***	1.395***	1.393***	1.388***	1.386***	1.395***	1.389***
	(20.22)	(20.02)	(19.48)	(19.69)	(19.51)	(19.58)	(19.38)	(19.36)
SMB	0.514***	0.495***	0.498***	0.504***	0.487***	0.493***	0.496***	0.487***
	(6.07)	(5.73)	(5.92)	(5.88)	(5.71)	(5.70)	(5.84)	(5.69)
HML	0.373***	0.335***	0.369***	0.374***	0.341***	0.344***	0.371***	0.346***
	(3.02)	(3.05)	(3.05)	(3.07)	(3.04)	(3.06)	(3.07)	(3.05)
Adj-Rsq	0.783	0.787	0.787	0.786	0.789	0.788	0.788	0.790

Panel C: Excess Winner Portfolio Return Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.624***	0.763***	0.768***	1.184***	0.822***	1.051***	1.160***	1.043***
	(6.65)	(7.39)	(7.11)	(5.90)	(7.89)	(6.05)	(5.89)	(6.06)
MKTILLIQ		-0.151***			-0.136***	-0.125***		-0.120**
		(-3.27)			(-2.87)	(-2.61)		(-2.48)
DOWN			-0.784***		-0.398		-0.445*	-0.247
			(-2.78)		(-1.31)		(-1.68)	(-0.85)
MKTVOL				-0.639***		-0.356*	-0.520**	-0.302
				(-3.19)		(-1.75)	(-2.53)	(-1.53)
RMRF	1.004***	1.010***	1.002***	1.002***	1.008***	1.008***	1.001***	1.007***
	(19.56)	(19.39)	(19.17)	(19.55)	(19.32)	(19.43)	(19.39)	(19.41)
SMB	0.267***	0.281***	0.274***	0.273***	0.284***	0.283***	0.276***	0.284***
	(4.05)	(4.49)	(4.29)	(4.25)	(4.56)	(4.51)	(4.34)	(4.55)
HML	-0.292***	-0.264***	-0.290***	-0.293***	-0.265***	-0.269***	-0.292***	-0.269***
	(-4.04)	(-4.17)	(-4.10)	(-4.17)	(-4.18)	(-4.22)	(-4.17)	(-4.21)
Adj-Rsq	0.757	0.763	0.759	0.761	0.764	0.764	0.761	0.764

Table 3: Individual Stock Momentum and Market States

Panel A presents the estimates of the following monthly Fama-MacBeth regressions,

$$R_{i,t} = \alpha_0 + \beta_{0t} R_{i,t-12:t-2} + \gamma_{1t} ILLIQ_{i,t-1} + \gamma_{2t} SIZE_{i,t-1} + \gamma_{3t} BM_{i,t-1} + e_{i,t},$$

where $R_{i,t}$ is the return of stock i in month t, $R_{i,t-12:t-2}$ is the accumulated stock return between month $t-12$ and $t-2$, $ILLIQ_{i,t-1}$ is the Amihud (2002) illiquidity, $SIZE_{i,t-1}$ is the market capitalization, and $BM_{i,t-1}$ is the book-to-market ratio. In Panel B, the estimated monthly β_{0t} coefficient is regressed on the time-series of lagged state variables: $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return:

$$\beta_{0t} = \alpha_0 + \gamma_1 MKTILLIQ_{t-1} + \gamma_2 DOWN_{t-1} + \gamma_3 MKTVOL_{t-1} + e_t,$$

The sample consists of all common stocks listed on NYSE and AMEX over the period 1928−2011. The Newey-West adjusted t-statistics are in parenthesis and numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Stock Return Regressed on Lagged Stock Return	
Intercept	0.785***
	(3.41)
$Ret_{t-12:t-2}$	0.008***
	(3.47)
ILLIQ	0.030**
	(2.40)
SIZE	-0.033*
	(-1.89)
B/M	0.134***
	(5.56)
Adj-Rsq	0.039

Panel B: β_{0t} Regressed on Lagged Market State Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	1.412***	1.226***	1.743***	1.514***	1.144**	1.636***	1.112**
	(5.39)	(10.96)	(4.13)	(9.98)	(2.16)	(4.29)	(2.20)
MKTILLIQ	-0.006***			-0.006***	-0.006***		-0.006***
	(-3.85)			(-3.14)	(-3.26)		(-2.93)
DOWN		-2.392***		-0.701		-2.036***	-0.981
		(-2.75)		(-0.58)		(-3.11)	(-1.06)
MKTVOL			-1.095*		0.332	-0.543	0.551
			(-1.78)		(0.36)	(-1.12)	(0.73)
Adj-Rsq	0.097	0.019	0.010	0.098	0.098	0.021	0.100

Table 4: Momentum Profits and the Cross-Sectional Illiquidity Gap

This table presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 ILLIQGAP_{t-1} + \beta_2 MKTILLIQ_{t-1} + \beta_3 DOWN_{t-1} + \beta_4 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t, $ILLIQGAP_{t-1}$ is the portfolio illiquidity gap between winner and loser momentum deciles, and the portfolio illiquidity is proxied by the average monthly equal-weighted stock-level Amihud (2002) illiquidity during the portfolio formation period ($t-12$ to $t-2$), $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). The sample period is from 1928 to 2011. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Momentum Profit (WML) Regressed on Lagged Portfolio Illiquidity Gap and Market State Variables						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.679***	1.708***	2.003***	2.993***	2.745***	2.743***
	(9.29)	(13.87)	(9.09)	(7.31)	(5.92)	(5.98)
ILLIQGAP		0.184***	0.101**	0.149***	0.098**	0.030
		(4.45)	(2.24)	(4.27)	(2.44)	(0.46)
MKTILLIQ			-0.338***		-0.246***	-0.220***
			(-9.40)		(-3.52)	(-2.97)
DOWN				-1.390***	-1.019**	-1.072**
				(-4.89)	(-2.25)	(-2.43)
MKTVOL				-1.185***	-0.731	-0.748
				(-3.08)	(-1.18)	(-1.23)
ILLIQGAP × MKTILLIQ						0.009**
						(2.03)
RMRF	-0.403***	-0.405***	-0.391***	-0.411***	-0.399***	-0.399***
	(-3.61)	(-3.63)	(-3.48)	(-3.53)	(-3.39)	(-3.39)
SMB	-0.238*	-0.237*	-0.204*	-0.211*	-0.196	-0.202
	(-1.82)	(-1.93)	(-1.76)	(-1.66)	(-1.60)	(-1.62)
HML	-0.650***	-0.646***	-0.584***	-0.645***	-0.600***	-0.598***
	(-3.60)	(-5.34)	(-5.81)	(-5.56)	(-5.85)	(-5.85)
Adj-Rsq	0.227	0.229	0.249	0.247	0.255	0.255

Table 5: Momentum in Big Firms and Market States

This table presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles for big firms in month t, $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). At the beginning of each month t, all common stocks listed on NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged eleven-month returns (formation period is from $t-12$ to $t-2$, skipping month $t-1$). For each momentum decile, big stocks are above the NYSE median based on market capitalization at the end of month $t-1$. The sample period is from 1928 to 2011, and all portfolio breakpoints are based on NYSE firms only. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Momentum Profit (WML) Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.569***	1.856***	1.923***	2.628***	2.030***	2.340***	2.555***	2.311***
	(8.38)	(8.96)	(8.71)	(5.97)	(9.64)	(5.33)	(5.98)	(5.37)
MKTILLIQ		-0.315***			-0.271***	-0.271***		-0.250**
		(-3.45)			(-2.79)	(-2.62)		(-2.37)
DOWN			-1.938***		-1.171*		-1.391***	-0.980*
			(-3.43)		(-1.86)		(-2.75)	(-1.79)
MKTVOL				-1.211***		-0.599	-0.836*	-0.384
				(-2.77)		(-1.09)	(-1.94)	(-0.75)
RMRF	-0.364***	-0.352***	-0.370***	-0.367***	-0.357***	-0.355***	-0.370***	-0.358***
	(-3.09)	(-2.93)	(-3.06)	(-3.07)	(-2.94)	(-2.93)	(-3.06)	(-2.94)
SMB	-0.022	0.008	-0.004	-0.010	0.015	0.010	-0.000	0.015
	(-0.16)	(0.06)	(-0.03)	(-0.07)	(0.11)	(0.07)	(-0.00)	(0.11)
HML	-0.630***	-0.571***	-0.625***	-0.632***	-0.576***	-0.580***	-0.628***	-0.581***
	(-3.17)	(-3.29)	(-3.21)	(-3.25)	(-3.29)	(-3.31)	(-3.25)	(-3.30)
Adj-Rsq	0.201	0.221	0.211	0.211	0.224	0.223	0.215	0.225

Table 6: Price Momentum, Earnings Momentum, and Market States in Recent Years (2001−2011)

This table presents the results of the following monthly time-series regressions,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted portfolio return (WML, winner minus loser deciles) from the momentum strategy in month t. In Panels B to D, stocks are sorted into deciles according to the lagged earnings news in each month (Panel B) or quarter (Panels C and D), and the Loser (Winner) portfolio comprises of the bottom (top) decile of stocks with extreme earnings surprise. In Panel A, WML refers to the winner minus loser portfolio sorted on past eleven-month stock returns. In Panel B, earnings news is proxied by the changes in analysts' forecasts of earnings (REV), and $REV_{it} = \sum_{j=0}^{6}(f_{it-j} - f_{it-j-1})/P_{it-j-1}$, where f_{it-j} is the mean estimate of firm i's earnings in month $t-j$ for the current fiscal year, and P_{it-j-1} is the stock price. In Panel C, earnings news is proxied by the standardized unexpected earnings (SUE), and $SUE_{it} = (e_{iq} - e_{iq-4})/\sigma_{it}$, where e_{iq} and e_{iq-4} refer to quarterly earnings per share for stock i in quarter q and $q-4$, σ_{it} is the standard deviation of unexpected earnings ($e_{iq} - e_{iq-4}$) over the previous eight quarters. In Panel D, earnings news is proxied by the cumulative abnormal stock return (CAR) from day -2 to day $+1$ around the earnings announcement, where day 0 is the announcement day and the abnormal return is stock return adjusted by the equally-weighted market return. $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). The sample period is from May 2001 to 2011. Newey-West adjusted t-statistics are reported in parenthesis and numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Price Momentum Profit Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.237	3.371***	1.575***	3.716**	3.371***	4.476**	3.770**	4.532***
	(0.35)	(2.91)	(2.94)	(2.50)	(2.93)	(2.52)	(2.31)	(2.63)
MKTILLIQ		-4.764**			-4.901**	-3.728**		-4.104***
		(-2.01)			(-2.44)	(-2.32)		(-3.06)
DOWN			-3.319*		0.222		-1.731	0.698
			(-1.96)		(0.16)		(-1.29)	(0.47)
MKTVOL				-2.933**		-1.507	-2.390*	-1.582
				(-2.26)		(-1.41)	(-1.70)	(-1.40)
RMRF	-1.034***	-1.082***	-1.070***	-1.083***	-1.081***	-1.097***	-1.093***	-1.094***
	(-3.83)	(-4.08)	(-3.91)	(-3.86)	(-4.10)	(-4.02)	(-3.91)	(-4.03)
SMB	0.531**	0.685**	0.647**	0.569**	0.682**	0.671**	0.622**	0.660**
	(2.00)	(2.44)	(2.31)	(2.22)	(2.31)	(2.47)	(2.32)	(2.32)
HML	-0.224	-0.285	-0.260	-0.466	-0.285	-0.396	-0.439	-0.399
	(-0.35)	(-0.44)	(-0.38)	(-0.64)	(-0.44)	(-0.57)	(-0.59)	(-0.58)
Adj-Rsq	0.253	0.323	0.282	0.301	0.323	0.332	0.307	0.333

Table 6—Continued

Panel B: Earnings Momentum Profit (based on REV) Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.120***	2.180***	1.767***	0.940*	2.179***	1.415**	1.007	1.325**
	(3.09)	(5.27)	(4.76)	(1.72)	(4.97)	(2.35)	(1.58)	(2.05)
MKTILLIQ		-1.611***			-1.126***	-2.328***		-1.713***
		(-3.15)			(-2.62)	(-3.51)		(-3.28)
DOWN			-1.603***		-0.789		-2.153***	-1.139*
			(-3.18)		(-1.38)		(-4.71)	(-1.94)
MKTVOL				0.152		1.043**	0.828	1.165**
				(0.29)		(2.18)	(1.62)	(2.49)
RMRF	-0.475***	-0.491***	-0.492***	-0.472***	-0.495***	-0.481***	-0.484***	-0.485***
	(-4.07)	(-4.31)	(-4.20)	(-3.91)	(-4.33)	(-4.24)	(-4.08)	(-4.26)
SMB	-0.223*	-0.171	-0.167	-0.225*	-0.159	-0.161	-0.159	-0.143
	(-1.81)	(-1.35)	(-1.29)	(-1.81)	(-1.22)	(-1.19)	(-1.15)	(-1.01)
HML	-0.343	-0.363	-0.360	-0.330	-0.366	-0.287	-0.298	-0.281
	(-0.94)	(-1.00)	(-0.94)	(-0.87)	(-0.97)	(-0.79)	(-0.76)	(-0.75)
Adj-Rsq	0.261	0.284	0.280	0.262	0.287	0.297	0.289	0.302

Panel C: Earnings Momentum Profit (based on SUE) Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.763**	1.389***	1.003***	0.843**	1.389***	1.093**	0.864*	1.097*
	(2.52)	(3.02)	(3.44)	(2.02)	(3.01)	(2.09)	(1.89)	(1.93)
MKTILLIQ		-0.951***			-1.054	-1.228***		-1.255*
		(-2.83)			(-1.38)	(-3.41)		(-1.71)
DOWN			-0.593		0.169		-0.694	0.049
			(-1.60)		(0.20)		(-1.46)	(0.06)
MKTVOL				-0.067		0.403*	0.151	0.398
				(-0.27)		(1.72)	(0.45)	(1.51)
RMRF	-0.270***	-0.279***	-0.276***	-0.271***	-0.278***	-0.275***	-0.275***	-0.275***
	(-3.46)	(-3.49)	(-3.45)	(-3.36)	(-3.60)	(-3.39)	(-3.33)	(-3.46)
SMB	-0.008	0.023	0.013	-0.007	0.020	0.027	0.014	0.026
	(-0.06)	(0.18)	(0.09)	(-0.05)	(0.15)	(0.20)	(0.10)	(0.19)
HML	-0.262	-0.274	-0.268	-0.267	-0.274	-0.244	-0.257	-0.245
	(-0.89)	(-0.92)	(-0.89)	(-0.89)	(-0.93)	(-0.83)	(-0.83)	(-0.83)
Adj-Rsq	0.184	0.202	0.190	0.184	0.202	0.206	0.190	0.207

Panel D: Earnings Momentum Profit (based on CAR) Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-0.170	1.198***	0.496**	1.200**	1.198***	1.555***	1.234**	1.545***
	(-0.57)	(3.93)	(2.23)	(2.25)	(3.92)	(2.79)	(2.16)	(2.68)
MKTILLIQ		-2.079***			-1.915***	-1.744***		-1.677***
		(-6.16)			(-3.44)	(-4.05)		(-2.68)
DOWN			-1.651***		-0.267		-1.117*	-0.125
			(-4.92)		(-0.38)		(-1.97)	(-0.17)
MKTVOL				-1.154***		-0.487	-0.804	-0.473
				(-3.11)		(-0.90)	(-1.52)	(-0.85)
RMRF	-0.297***	-0.318***	-0.315***	-0.316***	-0.319***	-0.322***	-0.323***	-0.323***
	(-4.53)	(-5.47)	(-5.08)	(-4.37)	(-5.61)	(-5.12)	(-4.77)	(-5.23)
SMB	0.242***	0.309***	0.300***	0.257***	0.313***	0.305***	0.291***	0.307***
	(2.83)	(3.72)	(3.18)	(2.97)	(3.69)	(3.62)	(3.13)	(3.61)
HML	-0.026	-0.052	-0.043	-0.121	-0.053	-0.088	-0.104	-0.087
	(-0.18)	(-0.41)	(-0.29)	(-0.72)	(-0.41)	(-0.56)	(-0.58)	(-0.55)
Adj-Rsq	0.120	0.200	0.163	0.165	0.201	0.206	0.180	0.206

Table 7: Momentum Profits, Sentiment and Macroeconomic Conditions

This table presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + \beta_4 Dummy(Low\ SENTIMENT)_{t-1} + \beta_4 M_{t-1} + \beta_5 CSRD_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t, $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return, $SENTIMENT_{t-1}$ is the monthly Baker and Wurgler (2007) market sentiment index, and $Dummy(Low\ SENTIMENT)_{t-1}$ is a dummy variable that takes the value of one if the investor sentiment is in the bottom tercile over the entire sample period. M_{t-1} refers to a set of macroeconomic variables including dividend yield, defined as the total dividend payments accruing to the CRSP value-weighted index over the previous twelve months divided by the current level of the index; three-month T-bill yield; term spread, defined as the difference between the average yield of ten-year Treasury bonds and three-month T-bills; and default spread, defined as the difference between the average yield of bonds rated BAA and AAA by Moody's. $CSRD_{t-1}$ is the three-month moving average of the monthly cross-sectional return dispersion ($t-3$ to $t-1$), constructed from 10×10 stock portfolios formed on size and book-to-market ratio, following Stivers and Sun (2010). The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), the book-to-market factor (HML), the Pástor-Stambaugh liquidity factor (PSLIQ), or the Chen, Roll, and Ross (CRR, 1986) five factors, including the growth rate of industrial production, unexpected inflation, change in expected inflation, term premium and default premium. The sample period is from May 2001 to 2010. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

	Momentum Profit (WML) Regressed on Lagged Market State Variables									
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	1.305*	4.157***	3.976***	22.186**	4.812**	4.039	4.678**	8.131**	2.729***	19.531*
	(1.71)	(2.82)	(2.86)	(2.56)	(2.38)	(1.63)	(2.08)	(2.29)	(2.70)	(1.67)
MKTILLIQ		-4.569**	-5.698**	-6.689***		-4.642***	-4.331***	-6.069**	-4.581**	-6.952***
		(-2.07)	(-2.18)	(-3.48)		(-2.89)	(-3.55)	(-2.08)	(-2.24)	(-3.59)
DOWN							1.062	3.481		0.805
							(0.61)	(1.39)		(0.44)
MKTVOL							-1.995*	3.631		1.919
							(-1.78)	(0.74)		(1.13)
Dummy (Low SENTIMENT)	-3.483*	-2.476*					-2.769*			-1.406
	(-1.76)	(-1.66)					(-1.83)			(-0.95)
SENTIMENT			3.232*							
			(1.84)							
CSRD					-1.395**	-0.197	0.384			
					(-2.26)	(-0.35)	(0.86)			
PSLIQ									0.571***	0.503***
									(4.08)	(3.72)
Macro Controls	No	No	No	Yes	No	No	No	No	No	Yes
FF Three-factor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
CRR Five-factor	No	No	No	No	No	No	No	Yes	No	No
Adj-Rsq	0.298	0.357	0.373	0.439	0.308	0.345	0.370	0.099	0.401	0.491

Table 8: Momentum Profits and Market Spreads

This table presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 MKTSPREAD_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t, $MKTSPREAD_{t-1}$ is the market spread, proxied by the value-weighted average of stock-level Corwin and Schultz (2012) bid-ask spread (with negative two-day spreads set to zero) of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). The sample period is from 1928 to 2011. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Momentum Profit (WML) Regressed on Lagged Market State Variables				
	Model 1	Model 2	Model 3	Model 4
Intercept	4.573***	4.226***	4.656***	4.302***
	(6.22)	(5.36)	(5.41)	(4.64)
MKTSPREAD	-5.131***	-4.110***	-5.629**	-4.559*
	(-3.96)	(-2.80)	(-2.33)	(-1.74)
DOWN		-1.197*		-1.194*
		(-1.81)		(-1.78)
MKTVOL			0.220	0.196
			(0.29)	(0.26)
RMRF	-0.397***	-0.398***	-0.398***	-0.399***
	(-3.38)	(-3.37)	(-3.37)	(-3.36)
SMB	-0.217	-0.212	-0.217	-0.211
	(-1.62)	(-1.58)	(-1.62)	(-1.59)
HML	-0.653***	-0.652***	-0.652***	-0.651***
	(-3.72)	(-3.72)	(-3.76)	(-3.76)
Adj-Rsq	0.254	0.256	0.254	0.257

Table 9: International Evidence on Momentum Profits and Market States

Panel A presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t in Japan, $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all firms listed in Tokyo Stock Exchange, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted market return in Japan during the past twenty-four months $(t-24$ to $t-1)$ is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily value-weighted market return in Japan. The vector F stacks Fama-French three Japanese factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). Panel B reports similar regression parameters in ten Eurozone countries, including Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain. Winner and loser portfolios are sorted within each country. The sample period is from 2001 to 2010. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Momentum Profit (WML) Regressed on Lagged Market State Variables (Japan)								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-0.381	1.789**	0.692	0.843	1.801**	1.527	1.111	1.522
	(-0.44)	(2.13)	(0.79)	(0.68)	(2.10)	(1.31)	(0.93)	(1.30)
MKTILLIQ		-57.681**			-50.825**	-60.154***		-53.277**
		(-2.45)			(-2.39)	(-2.69)		(-2.51)
DOWN			-2.202**		-0.554		-2.083**	-0.569
			(-2.09)		(-0.59)		(-2.19)	(-0.61)
MKTVOL				-0.925		0.268	-0.360	0.286
				(-1.21)		(0.46)	(-0.57)	(0.51)
RMRF	-0.122	-0.125	-0.142	-0.118	-0.130	-0.127	-0.140	-0.132
	(-0.56)	(-0.59)	(-0.64)	(-0.55)	(-0.59)	(-0.59)	(-0.64)	(-0.60)
SMB	0.424*	0.435**	0.427**	0.409*	0.435**	0.440*	0.421*	0.440*
	(1.86)	(1.98)	(2.02)	(1.74)	(2.00)	(1.96)	(1.93)	(1.97)
HML	0.629*	0.688**	0.662**	0.632*	0.690**	0.690**	0.661**	0.691**
	(1.97)	(2.38)	(2.25)	(1.96)	(2.39)	(2.40)	(2.23)	(2.41)
Adj-Rsq	0.103	0.148	0.128	0.109	0.149	0.149	0.129	0.150

Panel B: Momentum Profit (WML) Regressed on Lagged Market State Variables (Eurozone)								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.734	1.503*	1.594***	4.392***	1.905**	4.523***	4.407***	4.585***
	(1.57)	(1.97)	(2.70)	(8.73)	(2.50)	(8.62)	(8.77)	(8.70)
MKTILLIQ		-1.402**			-0.985*	-0.650*		-0.766**
		(-2.10)			(-1.88)	(-1.76)		(-2.07)
DOWN			-1.945***		-1.426***		0.236	0.589
			(-2.87)		(-3.07)		(0.43)	(1.24)
MKTVOL				-2.864***		-2.688***	-2.958***	-2.891***
				(-6.23)		(-5.51)	(-5.54)	(-4.80)
RMRF	-0.797***	-0.779***	-0.802***	-0.788***	-0.789***	-0.780***	-0.787***	-0.777***
	(-9.90)	(-9.29)	(-9.73)	(-8.57)	(-9.24)	(-8.42)	(-8.59)	(-8.55)
SMB	0.375	0.428	0.392	0.266	0.425	0.297	0.260	0.288
	(0.93)	(1.19)	(1.02)	(0.67)	(1.19)	(0.78)	(0.65)	(0.75)
HML	0.460	0.463	0.478	0.277	0.476	0.290	0.269	0.272
	(1.00)	(1.00)	(0.99)	(0.60)	(0.99)	(0.63)	(0.59)	(0.61)
Adj-Rsq	0.344	0.357	0.358	0.401	0.363	0.403	0.401	0.404

Figure 1: Time-Series of Momentum Payoff and Market States (2001 − 2011)

This figure plots the time-series of momentum portfolio payoff and market states, over the period between May 2001 and December 2011. At the beginning of each month t, all common stocks listed on NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged eleven-month returns (formation period is from $t-12$ to $t-2$, skipping month $t-1$) or lagged earnings news at month $t-2$, proxied by changes in analysts' forecasts of earnings (REV). The portfolio breakpoints are based on NYSE firms only. We report the average monthly value-weighted price momentum profits (WML, winner minus loser deciles) as well as earnings momentum profits (REV, extreme positive earnings surprise minus extreme negative earnings surprise deciles) in the holding period (month t). Market state variables (lagged at month $t-1$) include the aggregate market illiquidity ($MKTILLIQ$) and market return volatility ($MKTVOL$). $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return.